Rethinking Digital Divide of Building Information Modelling (BIM) Adoption in the Architecture, Engineering and Construction Industry

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Abstract

Extant research studies have attempted to evaluate the Building Information Modelling (BIM) divide in the Architecture, Engineering and Construction (AEC) industry; however, these studies are often premised on material access or technology-centric perspective. Consequently, this study examines the BIM divide from a multi-faceted perspective and evaluate its contextuality via firmographic variables. It mobilizes the digital divide model from the information technology discipline. The contextualized model depicts the BIM divide through four categories of motivational, physical, skills and usage access. The model was empirically tested through the Generalized Structured Component Analysis (GSCA) with data from an international questionnaire survey. The findings underscore the need to rethink BIM adoption as a multi-faceted and dynamic process against the extant static two-tiered representation. It highlights a notable BIM divide between firms in developed and developing economies. The findings necessitate further scrutiny of the effect of firms' size and age on BIM adoption and the unavoidable 'Mathew effect' of the BIM divide. Lastly, it provides paths in driving BIM implementation for stakeholders and policymakers and highlights the need to be context conscious in advocating for the transferability of global best practices in BIM adoption.

Keywords: Digital divide; BIM; developing economies, developed economies; SMEs

Introduction

In recent times, there has been a growing discourse that Building Information Modelling (BIM) meant to serve as an integrator in the construction industry is causing further fragmentations (Dainty et al., 2017) in the Architecture, Engineering and Construction (AEC) industry. The AEC industry can be said to be divided on a spectrum with regard to BIM adoption. These divisions are a result of the characteristic of BIM and varying access to BIM in the AEC industry. The access could be material access to BIM, diverse reasons to adopt BIM, varying skills, and usage opportunities (Cao et al., 2014; Jin et al., 2017). Despite these divides, the major focus in extant literature has been on material access to BIM. Thus, this study aims to evaluate the BIM divide from a multifaceted perspective and examine the influence of firmographic variables with a view of rethinking the current static representation of the BIM divide. It conceptualizes the BIM divide as inequalities in access to BIM in the AEC industry by mobilizing van Dijk (2005) Digital Divide model from the information technology field. This conceptualization is informed by theory and practice where there are diverse motivations for adopting BIM, varying BIM skill levels, and varying levels of BIM usage (Dainty et al., 2017).

The need for this study cannot be overemphasized as BIM has gained significant attention over the last decade. Its adoption has been associated with causing further fragmentation in the AEC industry. Thus, scrutinising the two-tiered representation of its adoption and BIM divide is necessary for evaluating the status quo and moving forward. The major contributions of this study are: (1) development and validation of a multifaceted divide of BIM in the AEC industry; (2) application of the digital divide concepts to BIM divide which has yet to be adequately explored and explained theoretically; (3) identification of contextualist perspective in BIM divide; (4)

identification of BIM divide effects; and (5) presentation of paths for driving BIM implementation for both stakeholders and policymakers. The forthcoming section presents a holistic review of BIM literature, followed by the theoretical background, research methodology, data analysis of the model, discussion of the findings, implications for practice and conclusions.

Literature review

Over the years, there has been an increase in BIM studies which can be broadly categorized per Gurevich and Sacks (2020) into industry level (Jiang et al., 2021), organisational level (Brito et al., 2021; Wang et al., 2020), project level (Liao et al., 2021; Ragab & Marzouk, 2021; Wang & Meng, 2021), and individual level (Ma et al., 2020). Although these extant studies have contributed to improving the understanding of BIM, the divide in adoption at the organisation level is unclear.

Table 1 presents a summary of BIM research studies from the organisation level in the AEC industry.

Insert Table 1

Hitherto the concept of BIM divide has not been explicitly evaluated in the BIM literature. The early connotation of BIM divide centred around a ‘two-tier system (Ashworth, 2012) and represent the divide between the adopters and non-adopters. Subsequently, the discussion moves toward ‘BIM compliant’ large firms and ‘BIM complaint’ small and medium-sized enterprises (SMEs). These discourses are often from a technocentric and deterministic view of BIM which is lacking in representation of reality and ignores the socio-technical context of BIM. Studies that have highlighted BIM divide often focus on material access or do not provide empirical justification (Ayinla & Adamu, 2018). Similarly, studies that have evaluated the influence of firmographics are often based on SMEs, a specified context, and often present contradictory findings(Chen et al., 2019).

Theoretical background

This study espouses the Digital divide model by van Dijk (2005) to explore the multifaceted divide of BIM in the AEC industry. This is because a) the concept extends divide beyond material access which is prominent in extant BIM discourse b) BIM is sociotechnical which resonates with the model’s concepts c) diverse motivations, varying skills and usage of BIM can be easily conceptualized d) the model constructs’ can be easily measured with matured constructs in BIM studies e) the model has been highlighted in extant discourses on BIM divide (Ayinla & Adamu, 2018; Dainty et al., 2017). The adopted model (van Dijk, 2005) proposes that the digital divide consists of four access which are motivational access, physical access, skill access and usage access that would better represent the concept of the digital divide (DE Haan, 2004). The following hypotheses are developed based on the model and evidence from extant BIM studies.

Hypothesis Development

Motivational Access

This relates to the motivation of the user for using BIM and includes the characteristics of BIM such as parametric modelling, lifecycle management, 3D visualization, and optimization which differentiate BIM from other CAD and ICT tools (Eastman et al., 2011). Aside from these characteristics, cultural, material, mental, social and temporal resources can also motivate firms to adopt BIM (Dainty et al., 2017; Won et al., 2013). Ahuja et al. (2016) identified motivation factors such as top management support, trust, and technical capability as significant factors affecting BIM adoption. Hong et al. (2018) corroborated those motivational factors such as reaping benefits from BIM adoption and usage opportunities as significant to the adoption of BIM in construction SMEs. From the foregoing the following hypotheses are proposed:

H1a: *The level of motivational access is positively related to the usage access of BIM in AEC organisations*

H1b: *The level of motivational access is positively related to the physical access of BIM in AEC organisations*

H1c: *The level of motivational access is positively related to the skills access of BIM in AEC organisations*

H7a: *Organisation type (Consultancy) is associated with the level of BIM motivational access*

Material (Physical) Access

Availability of hardware to support BIM does not equate to BIM usage in organisations. Arayici et al. (2011) opined that implementation of BIM goes beyond the mere installation of BIM tools which shows that the availability of BIM tools is a prerequisite. Similarly, Olatunji (2011) highlighted the importance of material access in BIM implementation. Also, extant studies (Ayinla & Adamu, 2018; Jin et al., 2017; Saka & Chan, 2020) have reported that one of the major challenges to BIM adoption is the physical access to BIM. Thus, logically material access would encourage BIM usage and the availability of BIM tools could encourage skill access of the firm which is per the assertions of Dainty et al. (2017). Based on these assertions the following hypotheses are proposed:

H2a: *The level of physical access is positively related to the usage access of BIM in AEC organisations*

H2b: *The level of physical access is positively related to the skills access of BIM in AEC organisations*

Skills Access

Adriaanse et al. (2010) opined that knowledge and skills are important access for usage of ICT in the construction industry. Especially for BIM, skills access is germane (Mahamadu et al., 2017) as it is a more technical tool and its implementation requires technical knowledge and skills.

However, lack of trained personnel has been identified as one of the major barriers to BIM implementation in the AEC (Sacks & Barak, 2010). Hong et al. (2018) termed skills access as knowledge support and found it significant for BIM adoption. However, Ding et al. (2015) termed it as knowledge structure and reported its insignificance in the adoption of BIM in architecture practice perhaps because such firms perceived BIM knowledge to be the default.

Based on these assertions the following hypothesis is proposed:

H3: *The level of skills access is positively related to the usage access of BIM in AEC organisations*

Usage Access

Organisations may have the motivation, physical or material and skills access and do not have opportunities to implement BIM. Studies have observed the influence of firm size, location of the firm, age of firm and organisation type on BIM usage access (Chen et al., 2019; Dainty et al., 2017; Hosseini et al., 2018). Large firms have more opportunities to use BIM and at a higher level of implementation compared to SMEs because of available resources and expertise (Ayinla & Adamu, 2018; Dainty et al., 2017). Similarly, firms in developed economies where there is support for BIM would have more usage access than firms in developing economies (Saka & Chan, 2021). Lastly, consultancy firms may have more usage access because it is easier to implement BIM at the design stage compared to the construction stage (Lam et al., 2017; Murguia et al., 2021; Olawumi & Chan, 2019). Thus, the following hypotheses are proposed:

H4d: *Size of firms (Large) is associated with the level of BIM usage access*
H5d: *Location of firms (Developed economies) is associated with the level of BIM usage access*
H6d: *Years of establishment of firms (higher) is associated with the level of BIM usage access*
H7d: *Organisation type (Consultancy) is associated with the level of BIM usage access*

Figure 1 depicts the theoretical framework with hypotheses and the control variables (location of firms, years of establishment, firm size, and organisation type) based on extant studies.

Insert Figure 1

Research Methodology

This study aims to evaluate the BIM divide in the AEC industry via the digital divide concept. Thereby examining the relationships between the four access of the digital divide and how the findings are per extant theories and studies. Consequently, a quantitative approach is employed to achieve the aim of this study. This approach is suitable for testing causal relationships and generalization of practical solutions which is typical of construction management studies (Wing et al., 1998) and when there is a prior theoretical commitment (Van Maanen, 1988)

Research Methods

The survey method is adopted for data collection in this study. The questionnaire survey has been well employed in innovation studies in the AEC industry. This is because of its benefit in assessing experts' opinions, experience, and its offer of quantifiability (Abdul Nabi & El-adaway, 2021; Wang et al., 2020). An empirical questionnaire survey was developed based on an in-depth literature review of extant studies of BIM adoption and implementation. The survey form presented the aim of the study and consists of two sections. The first section solicits information about the background of the respondents; the second section consists of questions in four subsections relating to each of the BIM divide access. The motivational access of BIM is measured with 9 items (Chen et al., 2019; Dainty et al., 2017; Hong et al., 2018), the physical access is measured with 2 items (Dainty et al., 2017; Olatunji, 2011), skill access is measured with 2 items (Ahuja et al., 2016; Hong et al., 2018) and the usage access measured with 4 items (Ahuja et al., 2016; Ayinla & Adamu, 2018). The identified variables for measuring the constructs are subsequently face validated and modified by experts and used in developing the questionnaire survey. The questions in these subsections were posited for rating to the respondents based on a five-point Likert scale which ranges from 1 = strongly disagree to 5 = strongly agree. A 5-point Likert scale is employed because it is adequate in representing experts' views (Chan & Kumaraswamy, 1997).

A pilot survey was conducted with construction professionals before the main survey administration to assess the appropriateness of the questions, and to identify ambiguities in the question structure. The following modifications were suggested a) Rewording of motivational access b) Changing material access to physical access d) Modifying the firm location from continent-based to country-based e) Firms size categorization should be based on employee size for uniformity. The questionnaire survey was edited and subsequently administered through an international survey targeted at diverse locations across the six continents.

Due to the challenges of determining the total population and sampling frame in an international survey, random sampling cannot be employed (Tariq & Zhang, 2020). Central limit theorem (CLT) postulates that the distribution of a sample variable approximates a normal distribution with an increase in sample size and is agnostic of the population distribution (Ross, 2020). Thus, a minimum sample size of 30 holds for the CLT and is often considered sufficient in surveys (Ott & Longnecker, 2015; Sproull, 1995). However, Fellows and Liu (2015) highlighted that for studies that would employ regression factor analysis, a minimum of 100 responses is required. Guadagnoli and Velicer (1988) suggested a minimum of 150 responses, and Schwab (1980) opined that the item to response ratio should be 1:10 (170 responses). Consequently, a minimum of 170 responses is targeted with a focus on the diversity of the responses.

Convenient and snowballing sampling techniques which are non-probabilistic approaches are adopted in this study. However, adequate caution is taken to avoid 'myside bias' and improve the heterogeneity of the responses (Patton, 2002). The survey link was sent to professionals on BIM groups on LinkedIn; professionals with BIM knowledge, construction firms that have participated in BIM projects were also contacted via emails from their website; and mails were sent to firms and professionals that were recommended by previous respondents.

A total of 367 entries was recorded for the questionnaire survey, after data cleaning, only 228 responses are deemed complete and meet the objective of this present study. This response is typical of web survey studies in construction management. (Ma et al., 2020). A sample size of 228 is considered adequate as the sample comprises varying organisation sizes from diverse locations and meet the thresholds. Also, the sample size of 228 with 17 items represent 1:13 which is above 1:10. Lastly, Kaiser–Meyer–Olkin (KMO) test was computed for sampling adequacy and the KMO value is 0.916 which is above the threshold of 0.70 (Kaiser, 1974).

Statistical Methods

Generalized structured component analysis (GSCA) which is a component-based approach to structural equation modelling (SEM) is employed to analyse the proposed model (Hwang & Takane, 2004). SEM is a technique that includes factor analysis, regression analysis, multiple correlations and path analysis (Hair et al., 2011). However, the component-based SEM evaluates the relationship between the variables and their weighted components (Cho et al., 2020). GSCA involves the specification of three sub-models which are measurement, structural and weighted relation model (Hwang & Takane, 2014). The general forms of these models are:

$$\text{Measurement model } \boldsymbol{z} = \boldsymbol{C}'\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \qquad (i)$$

Structural model $\boldsymbol{\gamma} = \boldsymbol{B}'\boldsymbol{\gamma} + \boldsymbol{\zeta}$ *(ii)*

Weighted relation model $\boldsymbol{\gamma} = \boldsymbol{W}'\boldsymbol{z}$ *(iii)*

Where z = *J* by 1 vector of indicators; γ = *P* by 1 vector of latent variables; C = *P* by J matrix of loadings; B = *P* by P matrix of path coefficient; W = *J* by *P* matrix of component weights; ε = J by 1 vector of the residual indicators; ζ = *P* by 1 vector of the residuals of latent variables.

These three sub-models are integrated into a single, general model referred to as a generalized structured component analysis model. The specification of the weighted relation model and the combination of the sub-models serves as one of the distinguishing differences between the GSCA and factor-based SEM and partial least squares path modelling (Cho et al., 2020). This combination enables easy use of model fit which is complicated in partial least square structural modelling where the measurement and structural model are estimated separately (refer to Hwang and Takane (2014) for extensive discussion on GCSA). The GSCA is employed in this study because a) the method leverages on the advantages of partial least squares path modelling b)the method overcomes the weakness of existing methods (Fornell & Bookstein, 1982; Jöreskog, 1970) c) it overcomes the challenges of lack of a global optimization criterion and provides an index to check the overall model fit (McDonald, 1996) d) the specified submodels are separately stated and combined to a single model with a single common optimization criterion e) it provides local fit indices to evaluate where misfits exist f) sample size and lack of normality of the data employed. Extant studies have applied the GCSA (Jung et al., 2016; Lemay & Doleck, 2020; Manosuthi et al., 2020) and empirical comparison of the method with other methods have been presented in the literature (Cho & Choi, 2019; Hwang et al., 2010; Jung et al., 2018). GSCA Pro 1.1.4 (software for GSCA analysis) is employed per the guide provided by Hwang et al. (2021).

Data analyses

This comprises the demographic distribution and the GSCA analysis.

Demographic distribution

Table 2 depicts the demographic information of organisations across the globe. The organisations are from varying practice and organisation types across the 6 continents of the world from 26 countries. Developed economies and developing economies (Nielsen (2011) per World Bank classification are represented and the sizes of the firms are equally distributed between the SMEs and the large firms. The Tables shows that the organisations are deemed suitable to respond to the questionnaire survey.

Insert Table 2

Generalized structured component analysis (GSCA)

This section presents the measurement model, structural model, model evaluation, and validation. The measurement model depicts the relationship between the latent variables and indicators while the structural model is based on the BIM divide model and depicts the relationship between the latent variables. Lastly, the model evaluation includes the overall model fit measures and local model fit measures.

Measurement model

The measurement model is evaluated for internal consistency (Cronbach’s alpha), convergent indicators (indicator reliability and proportional of variance explained (PVE)) and discriminant validity. Table 2 shows the evaluation of the internal consistency measure and the PVE.

Insert Table 3

Cronbach's alpha measures the internal reliability of the constructs based on the intercorrelations of the indicators and the value ranges from 0 to 1. From Table 3, the Cronbach's alpha value for all the constructs is above the threshold of 0.70 and these constructs can be considered to be reliable (Nunnally, 1978). The convergent validity, on the other hand, is a measure of the extent to which a variable correlates with alternative variables of the same construct (Hair et al., 2016) and it is often evaluated with the outer loadings of the indicators and PVE in GSCA. The PVE is the average amount of total variance of indicators that is accounted for by the components (Hwang et al., 2021). The values of the PVE are all greater than 0.50 indicating that on average the constructs accounted for more than 50% of the variance in the items.

Table 4 shows the estimates of component weights and component loadings of the indicators for each component. The table also presents the standard error for the bootstrap computed with 5000 samples along with the 95% confidence interval (CI) of the weights and loadings. The CI is used to test the significance of the estimate and an estimate is considered statistically insignificant at 0.05 level if its CI include 0. Thus, all the estimates for the weights and loadings are significant. Also, the loadings of all the items are above 0.60 which is acceptable. Although the Heterotrait-Monotrait (HTMT) ratio per pair of components computed were all lower than the 0.85 conservative threshold to signify discriminant validity (Henseler et al., 2014), however, the cross-loading was relied upon in this GCSA.

Insert Table 4

Structural Model

The structural model is evaluated based on collinearity, size and significance of path coefficient, coefficient of determination (R^2), and effect sizes (f^2) (Hair et al., 2016). The Variance inflation factors (VIF) was computed and the values are all below 5 which shows there are no collinearity issues with the components in the structural model. The bootstrapping procedure was performed with 5000 samples to compute the estimates, standard errors and statistical significance of the path coefficients. The effect size (f^2) measures the R^2 when an exogenous value is omitted to determine if it has a considerable effect on the endogenous construct. Cohen (2013) submitted that the effect sizes can be evaluated with thresholds of 0.02, 0.15, 0.35 representing small, medium, and large effects respectively.

Insert Table 5

The R^2 value of Physical access (0.517), skills access (0.692) and usage access (0.481) imply that substantial variances in the components are explained by the model. The values also indicate a substantial level of predictive accuracy and quality of the structural model (Hair et al., 2016). Table 5 present the estimates of the path coefficient and their bootstrap standard errors and 95% confidence interval. A path (coefficient) is considered significant at 0.05 level if its CI does not include 0. From Table 5, hypotheses H1a, b, c, H2b and H3 are all supported which implies that: motivational access influence on the usage of BIM physical access and skills access are significant; physical access influence on skills access is significant, and skills access have a significant influence on the usage access. Also, the hypotheses support that firms in developed economies are associated with physical and skills access; and consulting organisation types are more associated with physical access of BIM.

Per Cohen (2013), motivation access has a significant effect on physical access, skills access and usage access. Physical access has a significant effect on skills access, and skills access influences usage access. However, the effect of motivation access on physical access and the effect of physical access on skills access is considered a large effect.

Model evaluation

The GSCA provides the overall model fit measures and the local model fit measures. The overall model fit depicts the discrepancies between the model and data (Hwang & Takane, 2014). The GSCA employs FIT which is the proportion of the sum variance of all the indicators and variables accounted for in the model with a value that ranges from 0 to 1. The larger the value of the FIT, the more variance in the variables explained by the model. Consequently, the FIT value of 0.58 in this study depicted that 58% of the total variance of all the variables are explained in this model (Hwang et al., 2021). Also, the GFI (goodness-of-fit index) and SRMR (standardized root mean squared residual) are computed in GSCA. The GFI value is 0.98 and the SRMR value is 0.06 which meet the criteria per Cho et al. (2020) for sample size > 100 (GFI ≥ 0.93 and SRMR ≤ 0.08). Thus, this implies an acceptable fit for the model.

Local model fit measures reveal where misfits occur in the model and the GSCA provides separate measures for the measurement model (FIT_M) and structural model (FIT_S). The FIT_M and FIT_S values are 0.57 and 0.72 respectively. This implies that the measurement model accounted for 57% of the total variance of the latent variables while the structural model accounted for 72% of the total variances in the indicators. This shows that both the structural model and measurement model specified in this study are fit, although the structural model performed better than the measurement model.

Model validation

Although the model overall model fit and local model fit provides information about the model's fit, however, such indexes only provide information about how the specified model fit the sample. Thus, evaluating the model predictability beyond the sample data is necessary. Cross-validation is an approach for evaluating the prediction error of a model on a new sample that comes from the same population. This approach is recommended for evaluating models in SEM (Cho et al., 2019). The GCSA employs an out-of-sample prediction technique named ‘Out-of-bag Prediction Error (OPE)’ for cross-validation. It is computed by cross-validating the specified model over many sets of training and validation samples that are derived from the original sample through bootstrapping technique (Cho et al., 2019; Hair & Sarstedt, 2021). The validation of the developed model is highly recommended in management studies as previous indexes revealed more about the model explanatory power. The validation would present the predictory power of the model from which the managerial implications and recommendations can be reliably inferred (Hair & Sarstedt, 2021).

The OPE is computed by dividing each bootstrap sample into in-bag and out-bag samples, the specified model is then fitted with the in-bag sample, and the prediction error is computed with the out-bag sample. This procedure is repeated for the 5000 bootstrap sample and the OPE is the sum of all the predictions errors divided by the 5000. Thus, in this study, the OPE is computed for the measurement model (OPE_M) and structural model (OPE_S). The OPE for the model is 0.435, while the OPE_M is 0.287.

Discussion of Survey Findings

Motivational access of BIM

The findings support hypothesis H1a that the level of motivation access is positively related to the usage of BIM in the AEC organisations (β = 0.307, *95% CI (0.125 – 0.528)*). This corroborates the findings of Hong et al. (2018) that motivation affects BIM usage in firms. It is also in tandem with Ding et al. (2015) who similarly found motivation to be a significant factor that affects BIM implementation in AEC firms.

Notably, the motivation access of BIM has a large size effect ($f^2 > 0.35$) on physical access of BIM. The findings confirm the digital divide model's path that motivational access is positively related to physical access, skill access and usage access in tandem with the findings of van Deursen and van Dijk (2015). This reinforces the new proposition in this study that motivational access of BIM is related to other access (material, skill and usage). However, the findings of the study do not support hypothesis H4a which implies that large firm size does not relate with high motivational access. This corroborates Manley (2008) and Shelton et al. (2016) that small and medium-sized firms also have motivations to innovate like their large counterpart. The lack of support for H5a, H6a, and H7a implies that firms in developed economies, firms with longer years of establishment and consulting firms do not relate to a higher level of BIM motivational access. This is contrary to extant studies and could be a result of the more widespread adoption of the AEC in recent times. Albeit firms with varying sizes and locations may have different motivations (For instance, large firms might adopt BIM because of government mandate on their projects while SMEs may adopt BIM to improve efficiency), this is not under consideration in this present study.

Physical access of BIM

All the weight and loading estimates for the physical access are found to be significant at 0.05. Hypothesis H2a (*β = 0.103, 95% CI (-0.094 – 0.281)*) is found not to be significant which depicts that physical access does not directly correlate to usage access, however, hypothesis H2b (*β = 0.52, 95% CI (0.344 – 0.672)*) is supported. This is logical and agrees with Fleet (2012) that physical access is a necessary step towards the acquisition of skills and usage of technology. The findings imply that having access to hardware and software influences the skills access but material access on its own does not lead to usage.

Physical access has a large effect size on skills access per Cohen (2013) with f^2 of 0.37. Thus, it confirms the digital divide model's path proposed by van Deursen and van Dijk (2015). It also corroborates Goucher and Thurairajah (2012) that the inability to afford material access could impend BIM adoption as a significant barrier. Surprisingly, large firm size is not related to physical access (H4b not supported) which contradicts extant assumptions (Lam et al., 2015) that based on the limited resources of the SMEs, they do not invest in BIM. This challenges the notion of the two-tiered construction industry as regards size concerning material access. It implicitly shows that as there are large firms with physical access, there are SMEs with physical access in agreement with Ayinla and Adamu (2018). On the other, hypotheses H5b and H7b are supported by the findings, implying that firms in developed economies and consultancy firms are related to physical access of BIM. This is in tandem with the findings of Saka and Chan (2019) that there is a digital divide between developed economies and developing economies and between contracting firms and consultancy firms. This was premised on the availability of infrastructure in developing economies and the prior exposure of consultancy firms to computer-aided design (CAD) tools in agreement with Chen et al. (2019).

Skills access of BIM

The findings supported hypothesis H3 that skill access has a significant influence on the usage of BIM ($\beta = 0.367$, *95% CI (0.166 – 0.545)*) which is logical as skills are necessary to access usage of technologies. This is in tandem with the findings of Hong et al. (2018) that staff's BIM capacity affect BIM implementation. It also reinforces Hosseini et al. (2018) that the lack of trained personnel and lack of access to training and education could serve as a significant barrier to BIM adoption. However, the findings do not support hypothesis H4c that large firms are related to skill access, H6c that older firms are related to skill access and H7c that consultancy firms are related to skill access. This contradicts extant studies that firm size and age of firm affect the skill access of BIM. It shows that the challenges of trained personnel are size and age agnostic.

Hypothesis H5c is supported that firms in developed economies are related to skills access which is logical because of existing institutional support for BIM in such countries. More academic institutions are incorporating BIM into their curriculum to have BIM-compliant graduates in developed economies compared to developing economies. In addition, skill access has a significant size effect on usage access and significant predictive relevance. It confirms this study's proposition that skill access is linked to usage access of BIM and can serve as a driving path. Lastly, it highlights the skill divide between developed economies and developing economies in the AEC.

Usage access of BIM

Motivational access, physical access and skill access are all necessary access for BIM usage in the AEC organisations as supported by the hypotheses (H1a, H2a, and H3). Surprisingly, the study does not find evidence for the influence of firm's size (large) on BIM usage which contradicts the notion that large firms are more BIM complaints than SMEs. It contradicts extant assertions of a two-tiered construction industry between SMEs and large firms in BIM adoption. It contributes to the few studies that have questioned 'liability of smallness' with regard to BIM usage. Papadonikolaki and Aibinu (2017) revealed that the difference between firms in adoption goes beyond size and has more to do with organisational management. Similarly, Hosseini et al. (2018) corroborated that there is no significant relationship between SMEs size and level of BIM implementation. This finding broadly agrees with the work of Kimberly (1976) on organisation size.

Furthermore, the study does not find sufficient evidence to ascertain that firms' age influences BIM usage in contrast to Chen et al. (2019). Location of the firm has an indirect effect on Usage access through physical access and skill access reinforcing the proposition that there is a BIM divide between the developed and developing economies. Motivational access, physical access, and skill access have a significant influence on usage access with significant size effect and predictive relevance. Consequently, this confirms the digital divide model in the construction industry and agrees with studies from other disciplines such as van Deursen and van Dijk (2015). Most importantly, the findings confirm the multifaceted divide of BIM between the four access proposed. It provides a path for driving BIM in the AEC from a different perspective. Lastly, it highlights the growing skill divide and usage divide between developed and developing economies.

Implications for Practice

Although the dichotomous representation of the digital divide is parsimonious, it also oversimplified the concept. The findings necessitate the need to rethink BIM adoption as a multifaceted dynamic process and not a static adoption decision. The findings also imply that the BIM divide can be conceptualized using motivation, physical, skills and usage access. In addition, extant studies have reinforced the effect of firm size on BIM adoption in the construction industry, however, this study does not find sufficient evidence to support these assertions. This study however joins a growing number of studies (Ayinla & Adamu, 2018; Hosseini et al., 2018; Murguia et al., 2021; Papadonikolaki & Aibinu, 2017) that have highlighted the lack of a significant relationship between size and BIM implementation.

Although there is no doubt that the SMEs might face challenges in BIM implementation (Dainty et al., 2017), this does not mean they are mostly non-adopters as Manley (2008) enunciate that the SMEs can also adopt innovation successfully

Managerial Implications

The following practical managerial implications can be drawn from this study:

- There is a need to rethink the conceptualization of BIM divide beyond mere access to BIM tools and beyond the usage of BIM to include disparity in usage, motivation, and skills.
- The AEC industry can drive BIM adoption with a focus on motivations from the internal and external environments of the firms. However, firms should invest time and effort in implementing BIM to suit their organizational practices.
- Beyond material access to BIM, construction firms should devote effort in improving skills access in their firms. This can be achieved by providing more hands-on training sessions for staff and recruitment of staff that are digital practices oriented.
- SMEs can adopt and implement BIM like their large firm counterparts under the right contextual conditions. These SMEs can implement changes easily with less bureaucratic challenges when compared to large firms.
- The motivation, physical, and skills access of BIM might be easy to overcome but the usage access is more difficult to tackle and might lead to a 'usage gap' which would result in the 'Mathew effect' or 'Accumulation of Advantage (AOA)'. AOA relates to the fact that those that have early access would reap the benefits early and would continue to be motivated to make use of BIM. This necessitates the need to evaluate the 'Mathew effect' and 'accumulation of advantage' problem of BIM in AEC organisations.
- Construction firms and stakeholders should be context conscious in advocating for the transferability of BIM best practices in the AEC industry.

- Lastly, positing coercion as a motivation to drive BIM can have an unintended effect and lead to a further divide in the already fragmented industry. Thus, BIM policy should be sensitive to differences within the AEC sector and the culture of the industry.

Conclusions

This study mobilizes the digital divide model from the field of information technology to evaluate the BIM adoption and implementation in the AEC industry through an international survey of firms from 26 countries across the 6 continents of the world. The study confirms that the adoption of BIM could be explained through motivational access, physical access, skills access and usage access. The confirmation underscores the need to view the BIM adoption process as a multifaceted and dynamic process.

This study contributes to the body of knowledge by being the first to empirically evaluate the BIM divide that has been in extant BIM discourse and tested the influence of firmographic variables on the adoption process. It contributes to management domains by exploring the digital divide from BIM perspective which can be applied in other areas. It argues the need to re-evaluate the perception of SMEs being non-adopters and firms' age influencing BIM implementation. The study also underscores the need to be context conscious and the growing digital divide between the developed and developing economies as regards the physical and skills access of BIM. The developed model in this study has good explanatory power as revealed by the model fits and a good predictory power as revealed through cross-validation.

A possible limitation of the study is the respondents' size; however, due diligence was taken to ensure that the firms are from diverse backgrounds as much as possible. Adopting the digital divide model from the information technology is not hitch-free, as not all the possible views could be evaluated in this study. Further studies could evaluate the different motivational access of BIM in relation to firms' size, age and location. The usage access could also be assessed from the view of usage opportunities for firms. Lastly, the implications of the BIM divide which are the deepening divide and the Mathew effect need further scrutiny.

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Data Availability Statement

All data that support the findings of this study are available from the corresponding author upon reasonable request.

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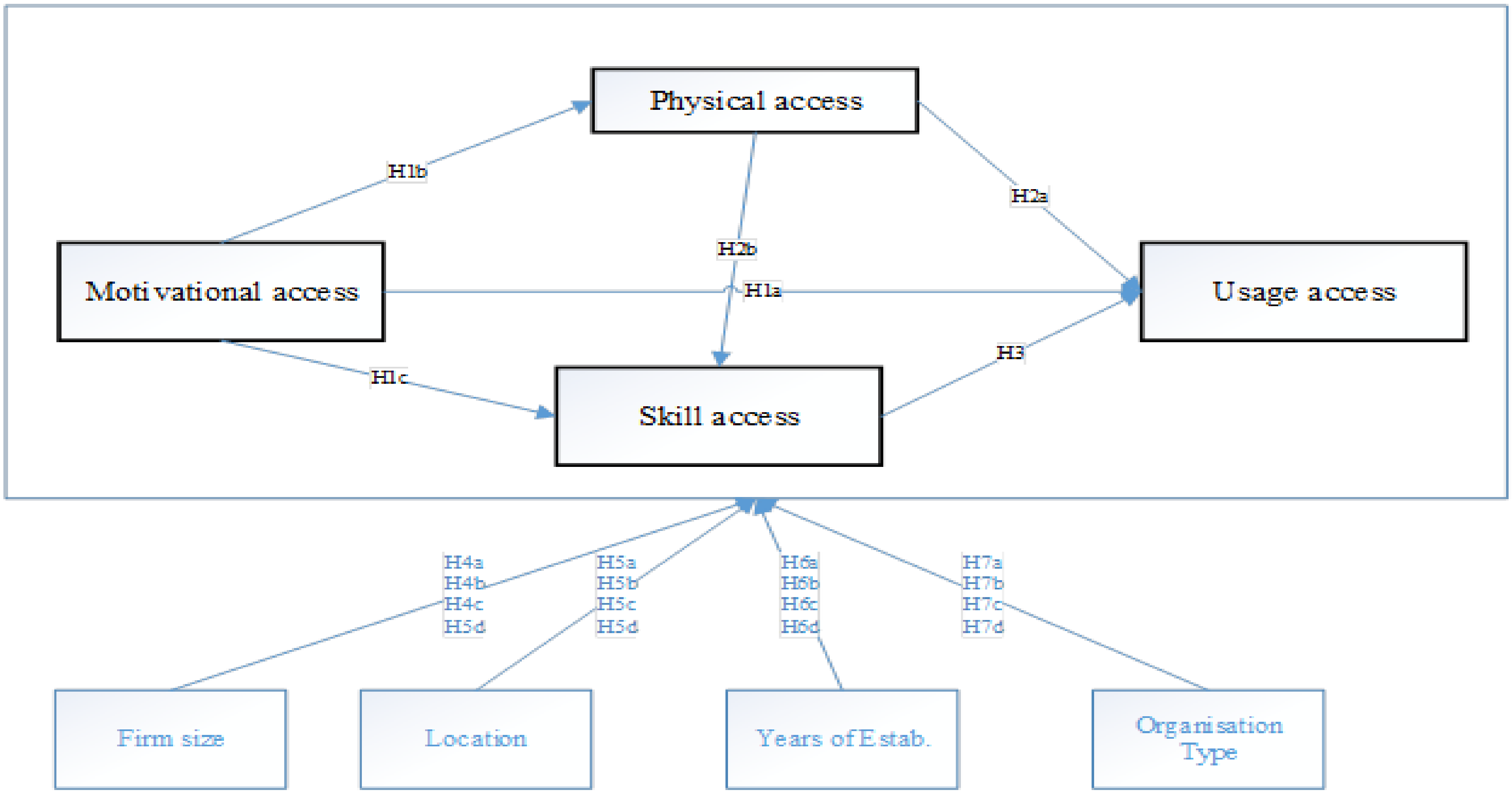

Figure 1: Overall Research Framework for the Study

Table 1: Summary of BIM Research Studies at Firm level in the AEC Industry

S/N	Studies	Focus
1	Aragó et al. (2021)	The study examines the implementation of BIM in quantity surveying practice and highlighted varying level of implementation across firm size. However, the study leaned towards skills and knowledge access of BIM and from Spanish context.
2	Brito et al. (2021)	The study developed BIM adoption framework based on critical success factors from technology, process, and policy categories. However, the study focused on public organizations from a developing country context.
3	Olatunji et al. (2021)	It examined the penetration of BIM in quantity surveying practices by examining the benefits and barriers of BIM adoption. However, the study does not provide the influence of firmographics and leans toward material access of BIM.
4	Hong et al. (2020b)	A neural network was developed to estimate the cost and benefits related to adoption of BIM in construction firms. Although the study collected data from different contexts, the influence of organization type is not considered.
5	Yuan and Yang (2020)	It explored the influence of government subsidy on BIM diffusion in the construction firms in the AEC. The study recognizes the effect of firmographics on BIM and captioned it as adoption efficiency, however, the study addresses BIM adoption from motivation access perspective.
6	Gurevich and Sacks (2020)	The study conducted a longitudinal study of BIM adoption and an improved version of BIM AIM (Adoption Impact Map) compiled. However, the study focused on adoption in public agencies.
7	Hong et al. (2020a)	It examined the cross-cultural differences in BIM adoption, however, the study focused only on size of firm (SMEs) in Australian and Chinese context.

8	Saka and Chan (2020)	The study presented barriers to BIM adoption with focus only on the SMEs from a developing country perspective.
9	Ma et al. (2019)	Similarly, this study highlighted barriers to BIM adoption in the Chinese context, however, no contextualization as regards firmographics.
10	Ayinla and Adamu (2018)	The study explored BIM divide in the AEC industry, however, the study focused on size in relation to material access.
11	Seyis (2019)	It presented the benefit, challenges, and risks of BIM adoption with focus on the SMEs.
12	Chen et al. (2019)	It employed technology-organization-environment framework to explore BIM in the Chinese context.
13	Hosseini et al. (2018)	It evaluated the usage access of BIM in the AEC with focus on the sizes in the Australian SMEs.
14	Ahmed and Kassem (2018)	The study examined BIM adoption in the AEC, however, it focused on architectural firms in the UK.
15	Dainty et al. (2017)	The study highlighted BIM divide via digital divide model, but no empirical evaluation was presented.

Table 2: Demographic Information of the Respondents

Characteristics	**Percentage (%)**
Main Practice	
Project Manager	14.04
Architect	13.60
Quantity Surveyor	13.60
BIM Manager	13.16
Developer / Client	10.96
Structural /Civil Engineer	9.65
Builder	8.77

Facility Manager / Estate Surveyor	8.77
Mechanical / Electrical Engineer	7.46
Years of organization establishment	
Less than 6 years	8.77
6 to 10 years	17.54
11 to 15 years	8.33
16 to 20 years	28.95
More than 20 years	36.40
Firm Size	
Small and Medium-Sized Enterprises (SMEs)	50.70
Large firms	49.30
Organization Type	
Contracting	46.32
Consultancy	53.68
Location Category	
Developed economies	49.12
Developing economies	50.88
BIM adoption in the organization	
We are not using BIM but plan to use it	39.47
We have used BIM but no longer using BIM	2.19
We are using BIM	58.33

Table 3: Measurement Items under Motivational, Physical, Skills and Usage Accesses

Construct	Item	Description	Cronbach's alpha reliability value	PVE
Motivational access	M1	BIM is compatible with our current work practice.	0.887	0.526
	M2	There are opportunities to use BIM in my firm		

	M3	My organization has capacity of using BIM		
	M4	BIM tools are easy to use in my firm		
	M5	There is no resistance to BIM usage in our organization.		
	M6	We trust BIM data.		
	M7	Our organization understands the benefits of using BIM		
	M8	Our firm is familiar with a variety of BIM software.		
	M9	Our organization provides incentives if we adopt or utilize BIM.		
Physical access	P1	Our organization provides enough hardware for BIM usage.	0.936	0.939
	P2	Our organization provides enough resources (software) for facilitating BIM usage		
Skills access	S1	There are well trained BIM personnel in our firm	0.842	0.863
	S2	My organization provides proper education/training for BIM utilization		
Usage access	U1	We produce 3D digital models with BIM	0.844	0.682
	U2	We work collaboratively on project design with BIM		
	U3	We share BIM models with design team members outside our organization		
	U4	We use a BIM model from the very start to the very end of a project		

Location	LO	Location of main practice	N/A	1
Organization type	OT	Type of main practice	N/A	1
Size	S	Number of employees	N/A	1
Years	YE	Years of establishment	N/A	1

Table 4: Component weights and Component loadings of the Measurement Items under Motivational, Physical, Skills and Usage Accesses

		Weights				**Loadings**			
	Item	**Estimate**	**SE**	**95% CI**	**U**	**Estimate**	**SE**	**95% CI**	**U**
Motivational access	M1	0.119	0.014	0.092	0.146	0.697	0.043	0.603	0.774
	M2	0.131	0.013	0.106	0.157	0.698	0.045	0.600	0.776
	M3	0.172	0.015	0.144	0.202	0.788	0.030	0.725	0.844
	M4	0.201	0.015	0.172	0.232	0.821	0.027	0.763	0.868
	M5	0.125	0.015	0.099	0.155	0.701	0.049	0.593	0.786
	M6	0.129	0.014	0.101	0.159	0.668	0.052	0.554	0.761
	M7	0.157	0.015	0.125	0.183	0.728	0.038	0.644	0.793
	M8	0.194	0.017	0.161	0.228	0.763	0.036	0.685	0.826
	M9	0.139	0.017	0.108	0.174	0.645	0.051	0.535	0.737
Physical access	P1	0.464	0.044	0.379	0.550	0.963	0.009	0.944	0.979
	P2	0.567	0.043	0.480	0.648	0.975	0.007	0.959	0.986
Skills access	S1	0.565	0.028	0.507	0.616	0.936	0.014	0.907	0.960
	S2	0.511	0.027	0.459	0.563	0.922	0.018	0.884	0.953
Usage access	U1	0.313	0.020	0.273	0.351	0.768	0.041	0.678	0.838
	U2	0.275	0.020	0.239	0.318	0.841	0.028	0.780	0.890
	U3	0.260	0.020	0.221	0.301	0.816	0.034	0.740	0.874
	U4	0.362	0.025	0.312	0.409	0.874	0.020	0.829	0.909
Location	LO	1	0	1	1	1	0	1	1

Organization type	OT	1	0	1	1	1	0	1	1
Size	S	1	0	1	1	1	0	1	1
Years	YE	1	0	1	1	1	0	1	1

Table 5: Results of hypothesis testing

Hypothesis	**Relationship**	**Std Beta**	**Std Error**	**95% CI**	**Decision**	**f^2**
H1a	*Motivational → Usage*	*0.307*	*0.103*	*(0.125 – 0.528)*	*Supported*	*0.10*
H1b	*Motivational →Physical*	*0.680*	*0.044*	*(0.594 – 0.763)*	*Supported*	*0.85*
H1c	*Motivational → Skills*	*0.297*	*0.078*	*(0.153 – 0.458)*	*Supported*	*0.10*
H2a	Physical → Usage	0.103	0.096	(-0.094 – 0.281)	Not Supported	0.01
H2b	*Physical → Skills*	*0.52*	*0.084*	*(0.344 – 0.672)*	*Supported*	*0.37*
H3	*Skills → Usage*	*0.367*	*0.097*	*(0.166 – 0.545)*	*Supported*	*0.16*
H4a	Firm size → Motivational	0.045	0.092	*(-0.136 – 0.233)*	Not supported	0.00
H4b	Firm size → Physical	0.083	0.058	(-0.029 – 0.196)	Not supported	0.01
H4c	Firm size → Skills	-0.080	0.055	(-0.193 – 0.023)	Not supported	0.01
H4d	Firm size → Usage	0.080	0.061	(-0.041 – 0.198)	Not supported	0.01
H5a	Location → Motivational	0.009	0.082	(-0.152 – 0.167)	Not supported	0.00
H5b	*Location → Physical*	*0.143*	*0.057*	*(0.031 – 0.253)*	*Supported*	*0.02*
H5c	*Location → Skills*	*0.173*	*0.054*	*(0.072 – 0.28)*	*Supported*	*0.03*
H5d	Location → Usage	-0.084	0.063	(-0.202 – 0.042)	Not supported	0.01
H6a	Years of estab → Motivational	0.027	0.089	(-0.156 – 0.198)	Not supported	0.00
H6b	Years of estab → Physical	-0.031	0.057	(-0.144 – 0.082)	Not supported	0.00
H6c	Years of estab →Skills	0.057	0.056	(-0.049 – 0.171)	Not supported	0.00
H6d	Years of estab → Usage	-0.043	0.061	(-0.167 – 0.077)	Not supported	0.00
H7a	Org. type → Motivational	-0.024	0.075	(-0.169 – 0.118)	Not supported	0.00
H7b	*Org. type → Physical*	*0.138*	*0.050*	*(0.039 – 0.238)*	*Supported*	0.02

H7c	Org. type → Skills	0.00	0.045	(-0.087 – 0.087)	Not supported	0.00
H7d	Org. type → Usage	-0.026	0.056	(-0.135 – 0.086)	Not supported	0.00